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Multi-source Information Fusion Technology and Its Engineering Application

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Abstract

With the continuous development of information technology in recent years, information fusion technology, which originated from military applications, plays an important role in various fields. In addition, the rapidly increasing amount of data and the changing lifestyles of people in the information age are affecting the development of information fusion technology. More experts and scholars have focused their attention on the research of image or audio and video fusion or distributed fusion technology. This article summarizes the origin and development of information fusion technology and typical algorithms, as well as the future development trends and challenges of information fusion technology.

Keywords

information fusion, data fusion, JDL data fusion process model, fusion algorithm

1. Preface

Information fusion originates from data fusion and can also be called multi-sensor information fusion. The original research on data fusion methods was for military applications, and the purpose was to correlate or combine multiple sensor data of the same or different types to obtain accuracy and credibility better than that provided by a single sensor. However, since the JDL (Joint Directors of Laboratories) data fusion process model researched by the US Department of Defense in the 1980s, data fusion has gradually developed into information fusion. Information fusion data sources are not limited to multi-sensor data, but both research and application areas have changed. In addition, with the rapid development of the network in recent years, the application of various algorithms has changed, which has also affected information fusion. For example, its research methods have changed from centralized single-node information fusion algorithm research to distributed information fusion research. There have been many studies on image fusion technology and research on big data fusion methods.

2. Information Fusion Brife

After years of research and development, information fusion has formed a definition that is recognized by many people. Although the expressions are not the same, it can be expressed as: Multi-source information fusion technology is a technology that uses computer technology to The information observed by each sensor is automatically analyzed and integrated under certain criteria to obtain valuable comprehensive information that cannot be obtained by a single or single type of information source, and finally completes its task target information processing technology (Yang, 2006).

Multisensor information fusion is essentially an imitation of the ability of the human brain to analyze and process data. In the analysis and observation of a variety of sensor data, the redundant information is sorted and the complementary information is integrated to obtain a more accurate description of the observation object.

The more authoritative definition of information fusion originally came from the US Department of Defense. Information fusion is also called data fusion. From the perspective of military applications, the US Department of Defense JDL (Joint Directors of Laboratories) defines information fusion as a process: data and information from many sensors and information sources are associated and correlated (correlation and combination to obtain accurate position estimation and identity estimation, as well as a proper complete evaluation of battlefield conditions and threats and their importance (Xiong, 2006)). Waltz and Llinas supplemented and modified the above definitions, replacing the position estimation with state estimation, and adding the detection function, giving the following definitions (Kang, 1997): Information fusion is a multi-level, multi-faceted The processing process includes the detection, correlation, correlation, estimation, and combination of multi-source data to obtain accurate state and identity estimates, as well as complete and timely battlefield situation assessment and threat assessment.

In the research and development of multi-source information fusion, information sources are always changing, not only from sensor data. In today's information-developed world, human brain activity and perception of the surrounding environment can be used as information sources. The diversity of information sources also puts forward higher requirements for information fusion.

Multi-source information fusion is the process of cognizing, synthesizing, and judging a variety of data. The principle of its realization is to simulate the processing of various information received by the human brain, and then, based on experience or relevant theoretical knowledge, The process of comprehensive analysis of data to make the final judgment. In multi-source information fusion, after the monitoring data of various sensors are processed to remove redundancy and spatial-temporal alignment, various data information is comprehensively processed according to a certain combination rule, and finally a consistent understanding of the monitored target Cognition.

The data processed in the multi-source information fusion system comes in various forms. It can be either original unprocessed data—data obtained by sensors, or processed data—data that is used to perform processing operations such as feature extraction on the data obtained by sensors. After processing the sensor data, the data can be transformed into parameters or state estimates that describe a process, can also be transformed into evidence for a proposition, or support a hypothetical decision. According to the level of data abstraction in the information fusion system, fusion can be divided into three levels: data-level fusion (also known as pixel-level fusion), feature-level fusion, and decision-level fusion.

2.1 Data-level Fusion

It directly fuses the original monitoring data from sensors of the same category, then extracts feature data, and finally performs recognition and judgment. The necessary condition for data-level fusion is that the sensor types must be the same, and only then can data-level fusion be performed. The data obtained by the fusion center during data-level fusion has the characteristics of large amount of data and high accuracy, but the requirements for system computing capacity and network communication speed are relatively high.

The fusion method often used in data-level fusion is the weighted average method. The weighted average method is a very simple and intuitive fusion method. The monitoring data provided by multiple sensors is multiplied by corresponding weights and then accumulated, and the sum is used as the fusion result. The biggest feature of this method is the small amount of calculation and the ability to fuse dynamic data in real time, but the setting and adjustment of weight coefficients are subjective and the work is tedious and complicated.

2.2 Feature-level Fusion

It belongs to the middle-level fusion, and can generally be divided into two types: information fusion of target features and information fusion of target states. Each sensor in the feature level fusion structure has the function of extracting features from the monitored data. Each sensor performs feature extraction on its own monitoring data, then submits it to the fusion center for fusion processing, and finally gives the attribute decision result.

The fusion algorithms often used in feature-level fusion include Kalman filter algorithm, joint probability data association, interaction model method, and sequential processing theory. The fusion of target feature information mainly uses clustering methods, neural network-based fusion methods, and so on.

The Kalman filter fusion algorithm uses the statistical characteristics of the measurement model to recursively determine the optimal fusion data estimate in the statistical sense, which is suitable for target tracking of linear systems, and generally suitable for stationary random processes. It requires the system to have a linear dynamic model, and the system noise and sensor noise are Gaussian distribution white noise models, and the amount of calculation is large, which is very sensitive to error data.

The core idea of clustering analysis fusion is to divide the target objects distributed in space according to a certain division rule.

Divided into several subsets, each subset can be determined to belong to a certain category according to the target characteristics. The cluster analysis algorithm is relatively subjective. It mainly depends on experience or defined functions to judge the quality of the clustering results. Therefore, in order to obtain more accurate clustering results, the effectiveness and repeatability of the clustering analysis algorithm must be analyzed before use.

The fusion method based on neural network uses the principle of neural network to fuse multi-source input information, which can better solve the problem of random error and system error of sensor system. The basic information processing unit of a neural network is a neuron, and the characteristics of the neuron determine the overall characteristics of the neural network in a certain program. Therefore, studying the characteristics of neurons is the basis of the fusion method using neural networks. The connections between neurons can have any form, so different neural networks can be constructed. Different neural network learning rules can be obtained by choosing different basis functions, activation functions, and weight adjustment methods. The most common structures are feedback neural networks (also known as forward neural networks) and neural networks without feedback.

2.3 Decision-level Integration

Where each sensor independently completes the feature extraction and recognition of the monitoring data rows, then submits the recognition results to the fusion processing center, and then the fusion processing center makes the final decision based on the recognition of each local fusion sensor. Decision-level fusion directly targets specific decision-making goals, and the results directly affect decision-making levels.

The fusion algorithms often used in decision-level fusion are: Bayes estimation, expert system D-S evidence theory, rough set theory, etc.

Bayes reasoning method. Think of each sensor as a Bayes estimator, which is used to synthesize the associated probability distribution of each target into a joint posterior distribution function, and then continuously update the hypothesized joint distribution likelihood function with the arrival of observations. And the final fusion of the information is performed by the maximum or minimum of the likelihood function.

Expert system DS evidence theory is a generalized Bayesian reasoning method. It expresses propositions through sets, transforms the uncertainty description of the propositions into the uncertainty description of the sets, and uses the probability distribution function, trust function, Likelihood function is used to describe the degree of objective evidence’s support for the proposition, and the reasoning and operation between them are used for target recognition.

In evidence theory, let A be a hypothesis or proposition in the recognition frame, and calculate the trust function and likelihood function about hypothesis A according to the basic probability distribution function formula. The interval representation of the function, where the trust function and the likelihood function are the lower and upper limits of the degree of trust in hypothesis A, and this closed interval represents the degree of confirmation of a hypothesis. The difference between the two indicates the degree of unclearness about a certain proposition or hypothesis, that is, the judgment of a certain proposition can be indeterminate except for positive or negative. Reducing the uncertainty interval is one of the purposes of evidence reasoning, and it intuitively shows the concept of uncertainty interval. The purpose of evidence synthesis is to reduce the uncertainty interval.

Rough set theory starts with the knowledge classification of the specified problem and discovers the inherent law of the problem. These operations do not require the relevant information of the attribute characteristics. Rough set theory has the ability of knowledge acquisition, knowledge analysis, decision analysis, discovery of internal relationships between data, elimination of compatible information, and simplified extraction of feature information and processing.

3. Development History

The development of information fusion has a long history, which can be traced back to the Bayes 'theorem published after Bayes' death in 1763, and Gauss used the least square method to estimate the orbit of the asteroid Ceres in 1795 using redundant data. With these two as a starting point, scholars have started research on the method of estimating the state based on data acquired by multiple sensors (Blasch & Plano, 2005). From here, the development of information fusion has roughly gone through the following three stages:

3.1 Early Simple Studies

Early research began with the publication of Bayes Theorem in 1963. The mathematical methods of information fusion have evolved from early signal and image processing to estimation methods, pattern recognition methods, automatic reasoning methods, Kalman filtering and other methods. Earlier research in the United States was a forerunner. With the support of the US Department of Defense, the US Army developed a military all-source analysis and fusion system, mainly for the study of sonar signals. The data source of the system is similar sensors, but also includes heterogeneous data in the same data form sensor. It mainly plays the role of strategic early warning to achieve target positioning and tracking.

3.2 Systematic and Structured Research

The second phase started with the creation of the JDL process model in 1990 (Kessler, 1992). Many papers have described the model, which has been widely cited in many books and textbooks. The model was first published in a report to the Navy's Intelligent Office, and later published as a paper, which had a great impact on later fusion systems.

In addition, seminars on various types of fusion systems have also been held, including the Tri-Service Data Seminar, the annual National Sensor Fusion Seminar (NSSDF), and the International Institute of Information Fusion (ISIF). In 2009, the China Information Fusion Branch (CSIF) was established. The holding of various academic conferences has created a good environment for the development of information fusion systems. The successive emergence of various fusion methods and fusion systems has also made the research system gradually perfect and mature. At the same time, information fusion has demonstrated its capabilities in non-military applications, and has gradually developed applications in the monitoring of complex systems, environmental monitoring, intelligent transportation and automobiles, healthcare and public health, computer and network security, and data privacy protection.

3.3 Fusion System with Human-Computer Interaction

At the beginning of the 21st century, more scholars are focusing on the connection between human users and converged systems. The operation of the fusion system is inseparable from the role that people play in the system. For example, human behaviors in the process of operating the system can have an effect on system optimization. Therefore, human-computer interaction has received considerable attention. Hall expanded the JDL model in 2000 and Plano in 2002, adding human-computer interaction. The purpose of the human-computer interaction fusion system is to make people’s role in the perceptual loop be controlled. In the process of system design, operation, and control, the user’s leading role is fulfilled through the combination of system and human capabilities to meet user needs.

3.4 Further Development of Converged System Architecture

In the past ten years, information fusion systems have been continuously adapted to the development of the information age. Many experts and scholars have put more effort into the research of fusion systems and methods such as image data source information fusion, big data-based information fusion, and distributed information fusion.

With the development of information technology, image acquisition and transmission have become very convenient, so the amount of image data provided by more sensors is increasing, which has led to more research on image fusion (Durrant-Whyte & Henderson, 2008). In addition, a wide range of intelligence sources and multi-form and multi-format intelligence obtained by various means have made information fusion based on big data urgently needed to be resolved. The distributed information fusion in response to network-centric warfare has also received widespread attention because it can be closely integrated with the battlefield environment in terms of effectiveness (Zadeh, 1999).

From the development history briefly summarized above, it can be seen that the research progress of information fusion technology has steadily advanced since its inception, and has had an important impact on the application and development of many fields. And with the development of computing technology, it also more urgently needs new technical means to adapt to the changing information age.

4. JDL Data Fusion Process Model

As mentioned in Chapter 2, in earlier research, the US Department of Defense funded the US Army to develop a military all-source analysis and fusion system. During this period, JDL was also an administrative agency that assisted research efforts between various laboratories of the US Department of Defense. The institution has established an affiliated institution dedicated to the problem of multi-sensor data fusion.

It is the JDL-affiliated institution that created the most typical model of data fusion, that is, the JDL model. This is also the originator of the data fusion model.

The initial briefing of the model only proposed three layers. After several modifications and optimizations, it gradually evolved into a six-level fusion model (Crisan & Doucet, 2002), including source preprocessing, object assessment, situation assessment, threat assessment, and process refinement. And cognitive refinement. The six levels are not isolated, but overlap, and the levels are not sequential, but overlapped. In addition, each level represents a type of information fusion, and each level also has a corresponding fusion technology.

4.1 Level Zero: Data Preprocessing

Zero-level processing is to pre-process the data obtained by sensors or people to facilitate subsequent fusion. This level of fusion technology is mostly data-level fusion, including image processing technology, post-absorption processing, coordinate transformation, filtering, and time-space alignment.

4.2 Level 1: Object Assessment

At this level, the system combines data changes to obtain the characteristics of the object, including location characteristics, behavior characteristics, identity characteristics, and so on. The objects here include physical targets such as vehicles, people, and ships, as well as target entities on the battlefield or other application areas. The technology in this part mainly comes from the research of target recognition.

4.3 Level 2: Situation Assessment

This level of fusion involves associating objects with their environment, or performing association analysis between different objects. For example, the movement of a car in a battlefield environment, or the action of a soldier, or the behavioral relationship between two cars. This level of fusion technology is mainly a method of fusing features, such as artificial intelligence, automatic reasoning, and pattern recognition.

4.4 Level 4: Process Refinement, Resource Management

The main goal of this level is to find ways to improve the fusion process. Through the analysis of sensor data and the perception of the current situation, the fusion process is improved by algorithms. This level of fusion technology includes sensor modeling, network modeling, computing performance, and optimized resource utilization.

4.5 Level 5: Human-Computer Interaction, Cognitive Refinement

The goals of this level are similar to the previous level, in order to find an optimized way to improve the interaction between the fusion system and people. At this level, the fusion system should pay attention to the human response after the system interacts with people, and make corresponding responses, so that people can play a more important role in the system. The types of processing can include advanced forms, search engines, consulting tools, cognitive assistance, collaboration tools, and so on. Among other things, geographic displays can be included. Data and overlays are displayed. Handles input commands and voice or haptic interfaces.

5. Typical Methods of Information Fusion

There are many classifications of information fusion algorithms, but no matter what the internal organizational structure or basic theory of the system is, the fusion algorithm must process the input data. Inspired by authors such as Khaleghi and others (Destercke, Dubois, & Chojnacki, 2009), this paper divides the fusion algorithms based on the input data of the system, and roughly divides them into three categories, that is, data with inherent disadvantages, data with correlations, and inconsistent data.

5.1 Defective Data

The method of processing the input data with inherent defects is a more important aspect of the fusion algorithm. Many researchers have also proposed information fusion algorithms based on dealing with such defects. These inherent flaws include uncertain data, inaccurate data, and data with inappropriate granularity. Different types of data are processed in different ways. For example, probability data can be used to deal with uncertain data, and fuzzy set theory can be used to deal with data fuzziness. If the input data contains multiple inherent defects, a hybrid approach can also be used. The following is a brief explanation of several methods that can handle inherent defect data.

5.1.1 Probability Method

This method uses a probability distribution to represent sensor data in a Bayesian framework. In this way, error information with a lower confidence level can be deleted (Zhu & Basir, 2006). This is a relatively complete method for dealing with data uncertainty, but it cannot solve the problem of data defects in other areas. The core of this method is to perform probability estimation based on Bayesian theory, and recursively fuse new data through the estimator to update the probability density of the system state (Wang & Chen, 2006).

The Kalman filtering method is a Bayesian filter in a special case, and has an accurate parser. For linear systems, when the noise generated by the system and the noise generated by the sensors can be modeled using white Gaussian noise, the Kalman filtering method can provide a statistically optimal fusion value. In addition, the Kalman filter is processed recursively, which ensures that the method can process data in real time and does not require excessive storage space.

5.1.2 Evidence Theory

Belief function theory originated from Dempster’s work after understanding and perfecting Gisher’s probabilistic reasoning method, and then mathematically formalized by Shafer into evidence-based general reasoning theory (Benavoli et al., 2007). Belief function theory is a framework for reasoning through theoretically convincing evidence. It is used to deal with the uncertainty and imprecision of data. D-S evidence theory is to assign credibility to possible hypotheses and fuse them with the required combination rules.

It can be considered as a generalization of Bayesian theory. However, this method is relatively inefficient when dealing with highly conflicting data.

5.1.3 Fuzzy Reasoning

Fuzzy inference algorithm is a method that allows fuzzy data representation, using fuzzy membership, and fusion based on fuzzy rules (Makarenko et al., 2009). This algorithm is an intuitive method for processing fuzzy data. However, the limitation of this algorithm is limited to the fusion of fuzzy data.

5.1.4 Possibility Theory

The algorithm was established by Zadeh and later extended and improved by Dubois and Prade. The algorithm is based on fuzzy set theory, but is mainly used to represent incomplete and non-fuzzy data. In fact, the possibility theory deals with incomplete data similarly to the methods of probability theory and D-S evidence theory. But this algorithm is not commonly used and is not easy to understand, so it is not widely used.

5.1.5 Rough Set

This algorithm was developed by Pawlak to express the information fusion brought by inaccurate data, and can ignore the uncertainty brought by different levels of granularity. It provides methods to approximate a target attribute with a predefined set of attributes under a specific framework. The use of this method makes the data need no preprocessing and no additional information, but the granularity of the data needs to be at a specific level.

5.2 Correlation Data

When multi-source data is input, not only will the input data contain inherent defects, but also data chaos or duplicate counts will occur. The inherent correlation between these input data will lead to deviations in estimation, such as duplicates Appearing data will generate high confidence (Maybeck, 1979). The possibility of such data appearing in distributed systems is particularly high, and in recent years, more information fusion systems have been developed in the direction of distributed systems. Therefore, data containing correlations need to be processed.

There are two main algorithms for the fusion of such data. The first is to delete identified duplicate data (Mclaughlin, Evans, & Krishnamurthy, 2003). There are probably two causes of duplicate data in a distributed system. One is that there may be multiple paths for information to be input from the information source to the system, and the other is that there may be duplicates in the loop where information returns from the output of the fusion node to the input. The handling of such situations is usually to set a specific network topology and a fixed communication delay, to prevent information from looping, or to reduce the possibility of repeated information encountering collisions.

The second algorithm is to process related data instead of deleting these duplicate data. This type of algorithm is suitable for more complex fusion scenarios. The most commonly used method is the Covariance Intersection (CI) method. This method was originally designed to deal with the underestimation of covariance matrices due to data incest. When processing two data sources, the method uses the estimated value of the covariance matrix as the combination of the mean and covariance of the input data.

5.3 Inconsistent Data

Inconsistent data is divided into four types, that is, fake data, unordered data, conflict numbers, and data from different sources. Next, a brief explanation of the solution for each type of data is given.

5.3.1 Pseudo Data

Pseudo data, which can also be called outliers, may be data transmitted by the sensor in unexpected situations. Such data may cause inaccurate results if added to the fusion process. There are two solutions, one is sensor verification technology (Wellington, Atkinson, & Sion, 2002; Ibarguengoytia, Sucar, & Vadera, 2007; Frolik, Abdelrahman, & Kandasamy, 2001). This method is based on the prior information to model a specific problem, and then to deal with different situations differently. However, the method is limited to a specific model of known faults. If a sensor fault occurs that has not occurred before, the performance of the method will be poor.

The second is a random adaptive sensor model (Kumar, Garg, & Zachery, 2006), which detects data without using prior knowledge. It is developed in the Bayesian fusion framework. The effect of calculation is to increase the variance of the posterior distribution, which has a better effect on the processing of pseudo data.

5.3.2 Out of Order Data

One of the corresponding algorithms for solving disordered data is to ignore, reprocess or use forward-backward prediction, but only if the data is assumed to have a single lag delay or a linear dynamic target (Orguner & Gustafsson, 2009). Another method is to use the enhanced state framework to incorporate delays, but this method is rarely mentioned in the literature.

5.3.3 Conflicting Data

There are usually two ways to resolve conflicting data. The first is to provide many alternative combinations of rules (Dezert, 2002; Lefevre, Colot, & Vannoorenberghe, 2002), but this method is usually not easy to implement without proper theoretical proof. Because the combination rule needs to meet three constraints: (1) an independent source that can provide independent evidence; (2) define homogeneous sources on a unique identification framework; (3) an identification framework that contains a unique, thoroughly hypothetical list.

The second is to continuously correct in the process of using evidence reasoning. As long as this method meets certain constraints, the validity of the rule can be maintained.

5.3.4 Data from Different Sources

The data sources input into a fusion system can be different, and may include sensory, human, or documented stored data. It is very difficult to fuse these data from different data sources to output complete, coherent and accurate information.

Nevertheless, in some fusion systems, different sensor data sources are necessary. For example, in the fusion system of human-computer interaction, human-transmitted "soft data" must be added (Hall et al., 2008). One aspect. Research on the fusion of soft and hard data, the current methods include D-S evidence theory, and the application of mixed strategies, but these studies are currently immature and need further development.

In addition to the information fusion processing algorithms for different input types mentioned in this section, typical algorithms for information fusion include relaxation methods, simulated annealing methods, genetic algorithms, and neural network-based methods.

6. Future Trends and Challenges of Information Fusion

In the current society, the changes and developments of information and networks have affected the design and application of information fusion systems to varying degrees. The realization of high-speed networks, the widespread popularity of smartphones, the continuous development of cloud computing and big data, breakthroughs in artificial intelligence, changes in human behavior and expectations, etc. have all put forward new requirements for information fusion systems.

At the same time, these aspects of innovation and development have brought new opportunities for data fusion and data acquisition. Distributed data fusion and image source information fusion have also become the focus of much attention in recent years. The difficulty of distributed data fusion lies in the architecture of the system architecture and the measurement of system indicators. At the same time, more information fusion systems highlight the role of human perception in the system. The user-involved fusion system can make the system closely integrate with the application and improve the performance of the system.

With the huge increase in the information society, breakthroughs in new technologies, and the creation of a large number of mobile Internet devices, new requirements have been imposed on information fusion systems. The challenges they currently face are:

6.1 Standardization and Characterization of Information Sources

Due to different sensor types, multi-sensor data sources need to be standardized and characterized, and the standardized data fusion effect in the fusion system will be better. In addition, in the development process of information fusion systems, human perception can also be used as a data source, but each different individual’s perception methods and standards are different. Therefore, the standardization and characterization of information sources is an important aspect of the design and implementation of fusion systems.

6.2 Develop Methods for Automatically Determining the Trustworthiness and Source Records of Information

Different sources of fusion system information have different degrees of trust. How to formulate an automatic method for determining information reliability and source records can have a significant impact on the fusion process. The source record of the information can also assist the fusion system to identify the source information. In addition, the automatic development of trustworthiness and source recording methods can also greatly reduce the manual impact on the fusion system.

6.3 Representation of Image and Video Data

In recent years, due to the rapid increase in the amount of data such as images and videos with higher quality, more and more fusion systems have begun to focus on analyzing data such as images and videos. The representation of this kind of information needs to automatically generate semantic metadata-data, which puts forward requirements for the image and video information extraction capabilities of the fusion system.

6.4 Meeting the Expectations of an Increasing Number of Cutting-edge Users

The addition of people to the information fusion system is not only a change in the source of the data, but the availability expectations of people on the fusion system also affect the fusion system. In a network society, people always use technologies such as the Internet, computers, and mobile phones. These "digital nationals" place additional demands on the collection and sharing of information.

6.5 From Data to Knowledge Fusion and More

The higher requirements for information fusion systems in the information age are not limited to the fusion of data and information, but can also develop into knowledge fusion or even higher levels. Knowledge representation methods have developed rapidly in recent years, and can be applied to multiple fields. Knowledge in information can also be fused in information fusion systems to make the results more formal.

7. Conclusion

The rapid development of information technology has changed the original fusion system in terms of data sources and fusion algorithms. Not only has the human factor played a more prominent role in the fusion system, but a large number of images, audio and video have also changed the format of the data source. In addition, the development of a large number of mobile devices has also made the input data more diverse. These changes make the converged system continue to develop and update on the original basis, and also bring a lot of confusion to the converged system.

The development of information fusion technology has a long history, and the algorithms and models involved are also very rich, and the application fields are also relatively extensive. This article studies the definition of the technology, its development, typical models, and typical algorithms. It also discusses the future development trends and difficulties of the technology.

With the development and change of these applied technologies, the research on fusion systems and algorithms will also continue to deepen. It is conceivable that the performance of the converged system will continue to improve in the future, and the application field will be wider.

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